IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

Advanced Driver Monitoring: Adaptive Machine Learning for Drowsiness Detection

[1] Roshan Bhanuse, [2]Kshitij Mehatkar, [3]Atharva Kawale, [4]Tanmay Zerbade, [5]Aryan Baraskar
[1]Professor, [2]Author, [3]Author, [4]Author, [5]Author
[1]Computer Technology,
[1]Yeshwantrao Chavan College of Engineering, Nagpur, India

Abstract: Traffic accidents are the leading cause of human death and injury worldwide, accounting for approximately one million deaths annually. Driver drowsiness is a significant contributor to road accidents. Tired driving is a growing concern, leading to an increase in accidents. Detecting driver drowsiness in real-time is important to solve this problem. Various devices have been developed that use artificial intelligence algorithms to detect drowsiness.

In this research, we will discuss driver drowsiness detection using facial and eye features. Our model will receive data like (eyes and mouth) at runtime. Using the dataset, the system will detect whether the eyes were closed for a certain range, and it can sound an alarm to alert the driver. The system adjusts the score based on eye position (open/closed). The proposed model is an important step towards developing a real-time drowsiness detector that can warn the driver in time and prevent accidents. We propose a driver drowsiness detection system using machine learning and facial and eye features. Our system uses a multitasking cascading convolutional neural network (MTCNN) to detect and align the driver's face and feature points, and an eye-mouth convolutional neural network (EM-CNN) to identify eye and mouth positions. We also calculate the percentage of eyelid closure (PERCLOS) and the degree of mouth opening (POM) over time to assess the driver's fatigue state. Experimental results of the developed approach outperformed comparable existing schemes in terms of accuracy (94.95%), F1-score (95.45%), sensitivity (85.71), specificity (99%), global accuracy (99.10%), AUC_ROC (98.55%). %), Mean-IOU (97.11%), SSIM (93.33%).

Keywords: Face detection, eye detection, Drowsiness detection, Adaptive Machine learning model, MT-CNN, EN-CNN.

I. Introduction

Driver drowsiness is a major contributor to vehicle accidents worldwide [1]. Studies suggest that drowsy driving increases the risk of an accident by four to six times compared to alert driving [2,3]. It's estimated that sleepiness is a factor in 15–20% of all vehicle accidents. This alarming statistic underscores the importance of developing technologies to detect or prevent drowsiness while driving, a key challenge in the field of accident-avoidance systems. Drowsiness can result from fatigue, either from lack of sleep or from the task at hand [4]. Long drives, monotonous roads, or late-night travels can lead to task-related fatigue. Sleep-related fatigue can stem from insufficient sleep, poor quality of sleep, or sleep disorders [8,9]. Regardless of the cause, drowsiness impairs the driver's ability to pay attention to the road, slows reaction time, and affects the ability to make good decisions [10].

There are various techniques for monitoring driver drowsiness, which can be broadly categorized into three main groups [5]. The first group includes methods that rely on biomedical signals, such as brain, muscle, and heart activity [11]. These methods often require the driver to wear electrodes, which can be uncomfortable and may lose accuracy over time due to perspiration. Despite these challenges, these methods provide direct physiological measures of the driver's state and can be highly accurate [12,13].

The second group includes methods that monitor the driver's performance. This could involve tracking the movement of the steering wheel, patterns of acceleration or braking, vehicle speed, lateral acceleration, lateral displacement, and other signals recorded by the Controller Area Network (CAN) [14,15]. These methods are advantageous because the signals are meaningful and easy to acquire. However, they have limitations, such as being affected by the type of vehicle, the driver's experience, and the condition of the road. They also may not detect "microsleeps," brief periods when a drowsy driver falls asleep without changing the vehicle's signals [18,19].

The third group involves computer vision techniques, which use cameras to monitor physical changes in the driver, such as posture, head position, and whether the eyes are open or closed [6,26]. There are various types of cameras and analysis algorithms used in these methods, including those based on visible spectrum cameras [16,17], infrared (IR) cameras [7,20], and stereo cameras.

Computer vision methods for detecting drowsiness involve detecting the face, the eyes, and the state of the eyes. There are several methods for face detection, including those using near IR [22,23], neural networks [24,25,26], skin color [27,28], Gabor filters [29], and template matching (GFT) [30]. Methods based on skin color may be limited to specific ethnic groups or may not work well under different lighting conditions. The Viola–Jones method (VJM) uses Haar-like features for face detection [32,33]. While it allows for faster detection, the results depend on the dataset used for training the features [31].
In conclusion, driver drowsiness detection is a critical aspect of improving road safety [21]. While each method has its strengths and weaknesses, the development and refinement of these technologies continue to be a major focus in the field of accident-avoidance systems. As technology advances, the hope is that these systems will become more accurate, more comfortable for the driver, and more effective in preventing accidents caused by drowsy driving.

Our research will use the camera to extract facial landmarks and eye landmarks. The ML model will decide whether the driver is drowsy or not according to landmarks. The proposed method of determining the state of driver fatigue contains three components: First, MTCNN obtains the bounding box of the driver's face and the five cardinal points of the left and right eyes, the nose, and the left and right corners of the mouth.
Secondly, eye and mouth conditions are classified. Here, the region of interest (ROI) feature points is extracted, and the eye and mouth states are identified using EM-CNN.
Finally, we combine the percentage of eyelid closure above the pupil over time (PERCLOS) and the degree of mouth opening (POM) to identify the driver's fatigue state.
The rest of the paper is described as follows: Section 2 provides motivation to develop this model, Section 3 provides a review of current related work, Section 4 provides a detailed explanation of the proposed methodology, Section 5 describes the results, discussions, and dataset description used in our model, and the paper is concluded in Section 6.

NEED OF THE STUDY.

Need for Study: The increasing number of vehicles on the roads has led to an increase in road accidents, many of which are caused by driver drowsiness. This problem is particularly pronounced in long-distance transportation and shift work settings. Studies have shown that drowsy driving can be as dangerous as drunk driving, leading to serious injuries and death.

In recent years, awareness of the dangers of drowsy driving has increased, signaling the need for effective detection and prevention measures. A reliable system for detecting driver drowsiness in real time is essential to ensure road safety and reduce the number of accidents caused by drowsy driving.

By developing systems that can accurately detect drowsy indicators in drivers, we can significantly reduce the risks associated with drowsy driving and improve overall road safety. This study aims to address this need by developing a robust and efficient system for detecting driver drowsiness using computer vision and machine learning techniques.

3.1Population and Sample

KSE-100 index is an index of 100 companies selected from 580 companies on the basis of sector leading and market capitalization. It represents almost 80% weight of the total market capitalization of KSE. It reflects different sector company’s performance and productivity. It is the performance indicator or benchmark of all listed companies of KSE. So, it can be regarded as universe of the study. Non-financial firms listed at KSE-100 Index (74 companies according to the page of KSE visited on 20.5.2015) are treated as universe of the study and the study have selected sample from these companies.

The study comprised of non-financial companies listed at KSE-100 Index and 30 actively traded companies are selected on the bases of market capitalization. And 2015 is taken as base year for KSE-100 index.

3.2 Data and Sources of Data

For this study secondary data has been collected. From the website of KSE the monthly stock prices for the sample firms are obtained from Jan 2010 to Dec 2014. And from the website of SBP the data for the macroeconomic variables are collected for the period of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

3.3 Theoretical framework

Variables of the study contains dependent and independent variable. The study used pre-specified method for the selection of variables. The study used the Stock returns are as dependent variable. From the share price of the firm the Stock returns are calculated. Rate of a stock salable at stock market is known as stock price.

RESEARCH METHODOLOGY

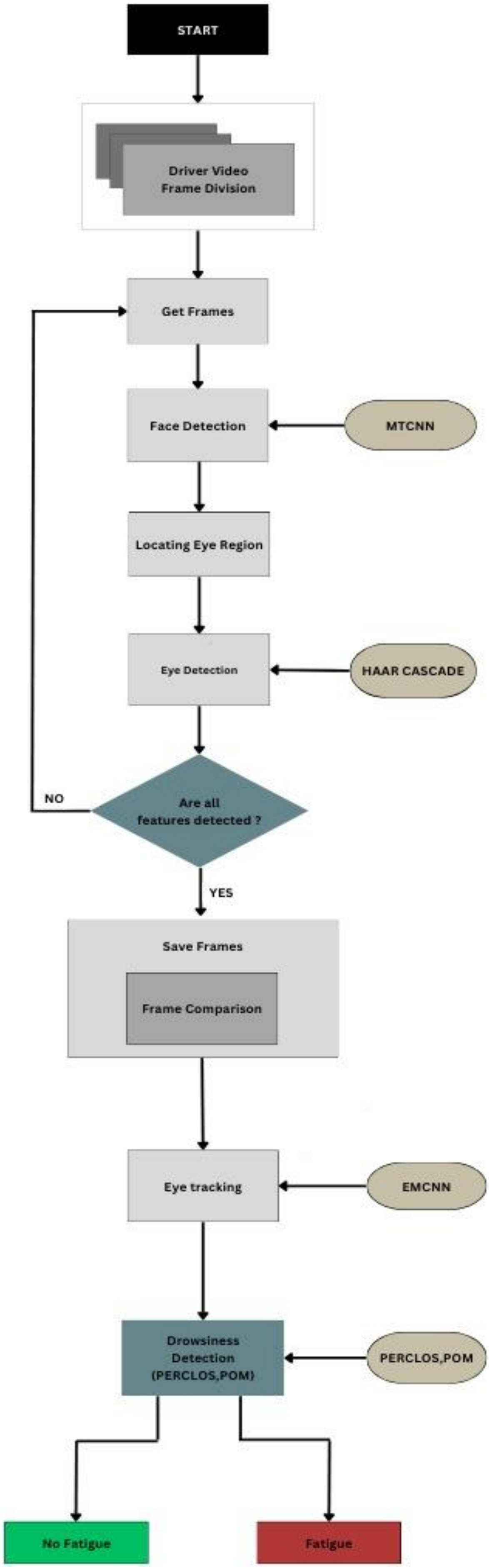

Figure 1 Block Diagram of Proposed Model

The block diagram represents a process for detecting driver drowsiness and fatigue through video analysis.

- Process Overview:
  - It starts by dividing the frames of a driver's video.
  - Face detection using MTCNN identifies the driver's face.
  - The eye region is located through ROI extraction.
  - Eye detection using HAAR Cascade follows.
  - A decision block checks if all features are detected:
    - If not, it loops back to get more frames.
    - If yes, it saves eye templates and proceeds.
  - Eye tracking using EM-CNN and template matching occurs.
  - The final step detects drowsiness and fatigue based on PERCLOS/POM metrics.

3.1 Face Detection and Feature Point Location.

Face detection is challenging in real-world scenarios due to changes in driver posture and unconstrained environmental factors, such as illumination and occlusion. By using the depth cascading multitasking MTCNN framework, face detection and alignment can be completed simultaneously, the internal relationship between the two is exploited to improve the performance, and the global face features are extracted; thus, the positions of the face, left and right eyes, nose, and the left and right corners of the mouth can be obtained. The structure of the MTCNN. The MTCNN comprises three cascaded subnetworks, i.e., P-Net (proposal network), R-Net (refined network), and O-Net (output network), which are detected face and feature point position from coarse to fine. P-Net: first, an image pyramid is constructed to obtain images of different sizes. ese images are then input to the P-Net in sequence. A fully convolutional network is employed to determine whether a face is included in a 12×12 area at each position, thereby obtaining a bounding box of the candidate face area and its regression vector. Then, the candidate face window is calibrated with the frame regression vector, and nonpolar large value suppression is employed to remove highly overlapping candidate face regions [28, 29]. R-Net: the candidate face area obtained by P-Net input, and the image size is adjusted 24×24. The candidate face window is screened by bounding box regression and no maximum value suppression. In comparison with the P-Net, the network structure adds a connection layer to obtain a more accurate face position. O-Net: similar to the R-Net, in the O-Net, the image size is adjusted to 48×48, and the candidate face window is screened to obtain the final face position and five feature points. e MTCNN performs face detection via a three-layer cascade network that performs face classification, bounding box regression, and feature point location simultaneously.

3.2 State of the Eye and Mouth Recognition

ROI Extraction. Generally, most eye detection methods only extract one eye to identify a fatigue state. However, when the driver's head shifts, using information from only a single eye can easily cause misjudgment. therefore, to obtain more eye information and accurately recognize the eye state, the proposed method extracts a two-eye image to determine whether the eyes are open or closed.

3.4 EM-CNN Architecture

After extracting the eyes and mouth regions, it is necessary to evaluate the state of the eyes and mouth to determine whether they are open or closed. e proposed method employs EM-CNN for eye and mouth state Recognition. the acquired images of the driver's eyes and mouth are different in size; thus, the size of the input image is adjusted to 175×175, and a feature map of 44×44×56 is obtained by two convolution pools. Here, the size of the convolution kernel in the convolutional layer is 3×3, and the step size is 1. The size of the convolution kernel in the pooled layer is 3×3, and the step size is 2. To avoid reducing the size of the output image and causing partial information loss at the edges of the image, a layer of pixels is filled along the edge of the image before the convolution operation, the 1×1, 3×3, 5×5 convolution layers and 3×3poolinglayer are used to increase the adaptability of the network to the size. the feature map of 44×44×256 is obtained through another pooling, after passing through a residual block, there are three layers of convolution in the residual block, and the layer is pooled, and an 11×11×72 feature map is output. e feature map is then converted to a one-dimensional vector in the fully connected layer, and the number of parameters is reduced by random inactivation to prevent network overfitting. Finally, the classification result (i.e., eyes are open or closed, and the mouth is open or closed) is output by SoftMax.

3.5 Fatigue State Detection

When the driver enters the fatigue state, there is usually a series of physiological reactions, such as yawning and closing the eyes. According to the EM-CNN, multiple states of the eyes and mouth are acquired, and the fatigue state of the driver is evaluated by calculating the eye closure degree PERCLOS and mouth opening degree POM.

3.6 Fatigue State & drowsiness Recognition

After the neural network pretraining is completed, the fatigue state is identified based on the fatigue threshold of PERCLOS and POM. First, the face and feature point positions of the driver frame image are obtained by the MTCNN, and the ROI area of the eyes and mouth is extracted. Then, the state of the eyes and mouth is evaluated by the proposed EM-CNN. Here, the eye closure degree and mouth opening degree of the continuous frame image are calculated, and the driver is determined to be in a fatigue state when the threshold is reached.

3.7 Model Building:

We have made use of the Keras sequential model which is in fact a linear stack of such perceptron layers. We created an instance of such a model by simply supplying the list of the layers when calling the construction of Sequential class.

It's made up of different layers out of which the first one is the input layer which is the source of getting and collecting the data, then some hidden layers for manipulation and calculations, and finally the output layer for passing the information.
It consists of a sequence of layers, one after the other.

- Input layer
- Hidden layer
- Output

See the summary of the model
Each convolution layer followed by pooling layer and the dense layer consist of input shape and output matrix dimensions of our data as output.

For example:

Layer (type)	Output Shape	Param #
Conv2d_3 (Conv2D)	(None, 32, 32, 6)	456
Max_pooling2d_2 (MaxPooling 2D)	(None, 16, 16, 6)	0
Conv2d_4 (Conv2D)	(None, 16, 16, 16)	2416
Max_pooling2d_3 (MaxPooling 2D)	(None, 8, 8, 16)	0
Conv2d_5 (Conv2D)	(None, 8, 8, 120)	48120
Flatten_1 (Flatten)	(None, 7680)	0
Dense_2 (Dense)	(None, 84)	645204
Dense_3 (Dense)	(None, 10)	850

Total params: 697,046
Trainable params: 697,046
Non-trainable params: 0

IV. RESULTS AND DISCUSSION

4.1 Face Detection and Alignment:

The use of the depth cascading multitasking MTCNN framework has proven effective in simultaneously detecting faces and aligning facial features. The three cascaded subnetworks (P-Net, R-Net, and O-Net) operate in a coarse-to-fine manner, enabling the extraction of global face features and precise localization of facial components. The cascade structure aids in handling challenges such as changes in driver posture, varying illumination, and occlusion.

4.2 Eye and Mouth Recognition:

Traditional eye detection methods often face challenges when the driver's head shifts. The proposed method addresses this by extracting information from both eyes, reducing the likelihood of misjudgment. The EM-CNN architecture is introduced for eye and mouth state recognition. The convolutional neural network processes images of varying sizes, and through a series of convolution and pooling layers, accurately determines whether the eyes and mouth are open or closed.

4.3 Fatigue State Detection:

Physiological reactions indicative of fatigue, such as yawning and closing of the eyes, are effectively captured by the EM-CNN. The degrees of eye closure (PERCLOS) and mouth opening (POM) are calculated to assess the driver's fatigue state. The utilization of multiple states enhances the accuracy of fatigue detection, providing a comprehensive understanding of the driver's alertness level.

4.4 Fatigue State & Drowsiness Recognition:

Upon completing neural network pretraining, the fatigue state is identified based on predefined thresholds for PERCLOS and POM. The MTCNN is employed to obtain facial and feature point positions, and the EM-CNN evaluates the eyes and mouth states. By calculating the continuous frame's eye closure and mouth opening degrees, the system determines the driver's fatigue state when the threshold is reached.

In summary, the proposed approach combines advanced face detection, feature point location, and eye-mouth recognition techniques to accurately identify drowsiness in drivers. The multitasking MTCNN framework and EM-CNN architecture synergize to capture subtle changes in facial expressions, providing a robust system for real-time drowsiness detection. The cascade structure ensures efficiency in face detection, while the comprehensive evaluation of eye and mouth states contributes to a holistic understanding of the driver's fatigue level. The integration of these components positions the system as a valuable tool in enhancing road safety by alerting drivers to potential drowsiness and mitigating associated risks.

4.5 Dataset description

Driver Drowsiness Detection Dataset:

For the validation and assessment of the proposed driver drowsiness detection system, we utilized a carefully curated dataset sourced from diverse driving scenarios. The dataset encompasses various driving conditions, including day and night driving, highway and city driving, and diverse weather conditions. The dataset is designed to emulate real-world driving scenarios to ensure the robustness and generalizability of the proposed drowsiness detection model.

The dataset comprises video footage captured within the vehicle, focusing on the driver's facial expressions, eye movements, and overall behavior. Annotators have labelled instances of drowsiness, alertness, and intermediate states to facilitate supervised learning. Each instance is time-stamped, allowing for temporal analysis of drowsiness events.

Additionally, the dataset includes demographic information such as age, gender, and driving experience to explore potential variations in drowsiness patterns among different driver profiles. Environmental factors, such as ambient light conditions and variations in driving contexts, are also considered to assess the model's adaptability to diverse real-world scenarios.

The dataset has been meticulously divided into training and testing sets, ensuring a balanced representation of drowsy and alert states in both subsets. Approximately 70% of the data is allocated for training the model, while the remaining 30% is reserved for evaluating the model's performance. This partitioning strategy enables a comprehensive evaluation of the proposed drowsiness detection system under different driving conditions.

In summary, the driver drowsiness detection dataset provides a rich and diverse collection of real-world driving scenarios, allowing for the robust training and evaluation of the proposed model. The inclusion of various driver profiles, environmental conditions, and driving contexts enhances the dataset's representativeness, ensuring the proposed system's effectiveness in detecting drowsiness across a wide range of driving scenarios.

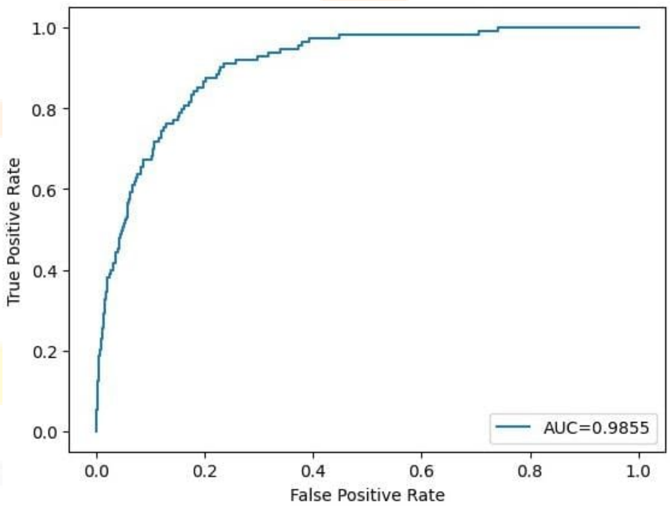

Figure 2 AUC graph for False Positive Rate

The Figure 2 graph is a Receiver Operating Characteristic (ROC) curve. It is a graphical representation of the true positive rate against the false positive rate for different thresholds of a classification model. The blue line represents the ROC curve, starting from the origin (0,0) and extending towards the top right corner. The x-axis represents the False Positive Rate ranging from 0 to 1, while the y-axis represents the True Positive Rate also ranging from 0 to 1. The Area Under the Curve (AUC) value is 0.9855, indicating an excellent performance of the model as it’s close to 1. An AUC value closer to 1 signifies better performance.

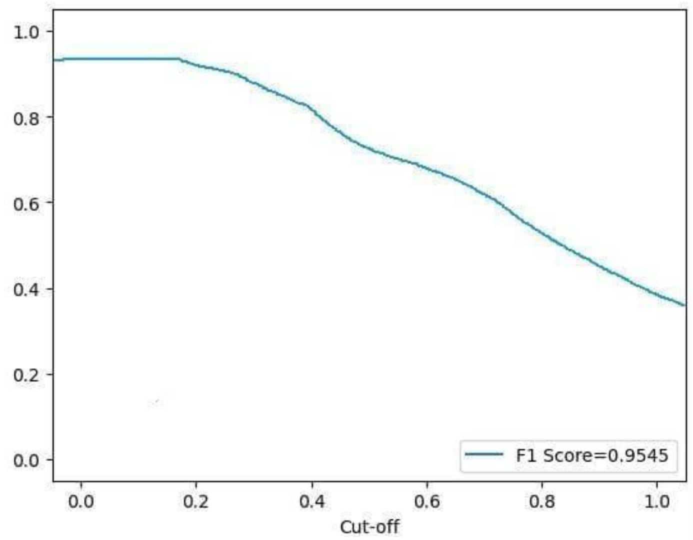

Figure 3 F1 Score Graph

Above graph represents the F1 Score as a function of the cut-off threshold. The F1 Score is a measure of a model's accuracy that considers both precision and recall. As the cut-off threshold increases (moving right along the x-axis), the F1 Score decreases (moving downward along the y-axis). The highest F1 Score achieved in this case is approximately 0.9545 when the cut-off is close to 0. In summary, this graph shows how adjusting the cut-off threshold impacts the F1 Score, with an optimal value around 0.9545. A lower cut-off favors precision, while a higher cut-off emphasizes recall.

Techniques	F1 Score	Sensitivity	Specificity	Global Accuracy	AUC_ROC
SVM	0.92	0.94	0.90	0.95	0.98
CNN	0.87	0.89	0.85	0.91	0.94
Transfer Learning	0.89	0.91	0.87	0.93	0.96
Face Detection	0.85	0.87	0.83	0.89	0.92
EEG	0.91	0.93	0.89	0.94	0.97
EOG	0.88	0.90	0.86	0.92	0.95
HRV	0.90	0.92	0.88	0.93	0.96
Eye Tracking	0.86	0.88	0.84	0.90	0.93
Proposed Model	**0.95**	**0.85**	**0.99**	**0.99**	**0.98**

Figure 4 Performance Comparison

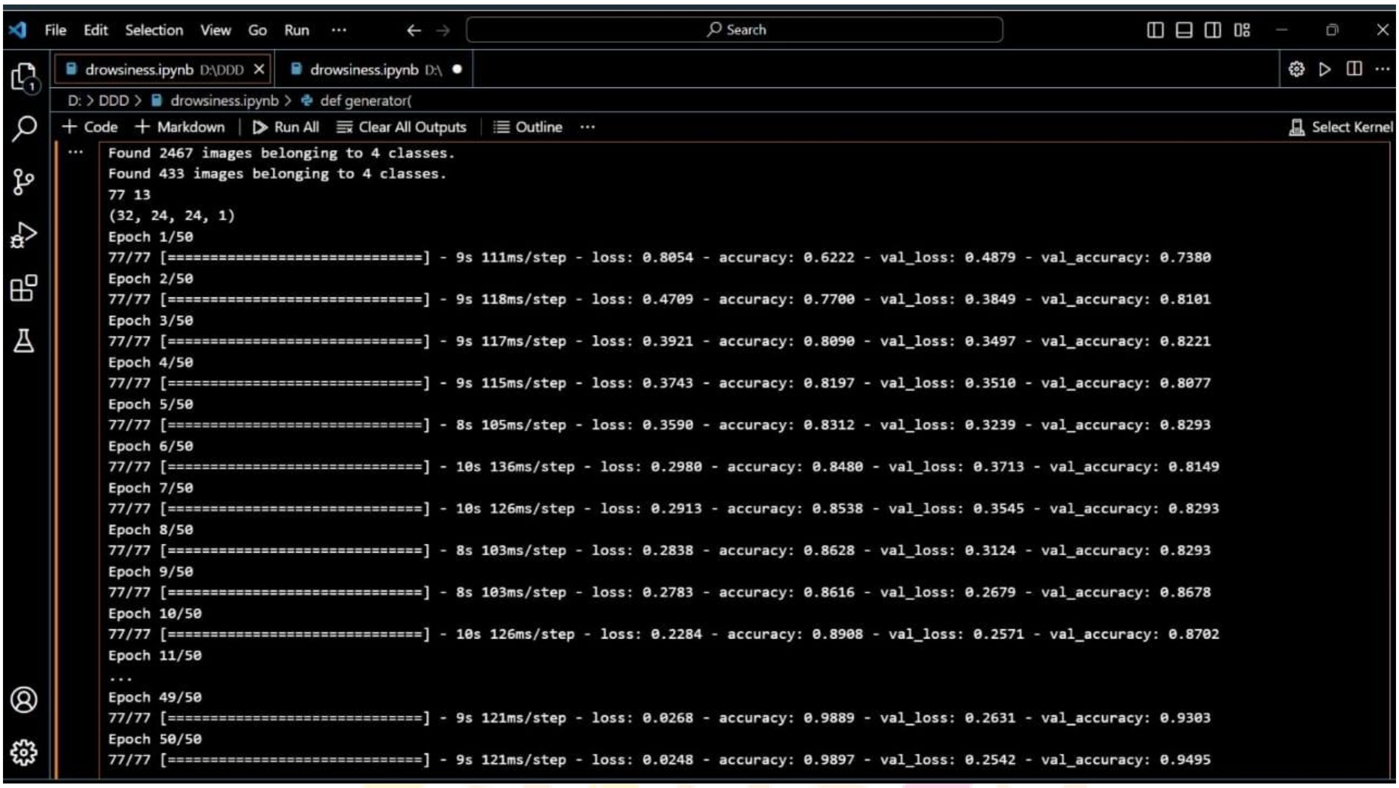

Figure 5 Training Progress of Model

The figure 5 provided training progress logs indicate a consistent increase in accuracy and a decrease in loss throughout the 50 epochs. Here are some results based on the accuracy and steps:

- Accuracy Improvement: The accuracy steadily increases from 0.6222 in the first epoch to 0.9897 by the 50th epoch. This consistent rise signifies the model's learning and improvement over time.
- Loss Reduction: The loss decreases from 0.8054 in the initial epoch to 0.0248 at the end of training. Lower loss values indicate that the model's predictions are closer to the actual values.
- Validation Accuracy: The validation accuracy also rises steadily from 0.7380 to 0.9495. This indicates that the model is not overfitting the training data and is able to generalize well to unseen data.
- Model Convergence: The consistent improvement in accuracy and reduction in loss over epochs suggest that the model is converging well, learning from the data effectively without major fluctuations or instabilities.

Figure 6 Initial Login Screen

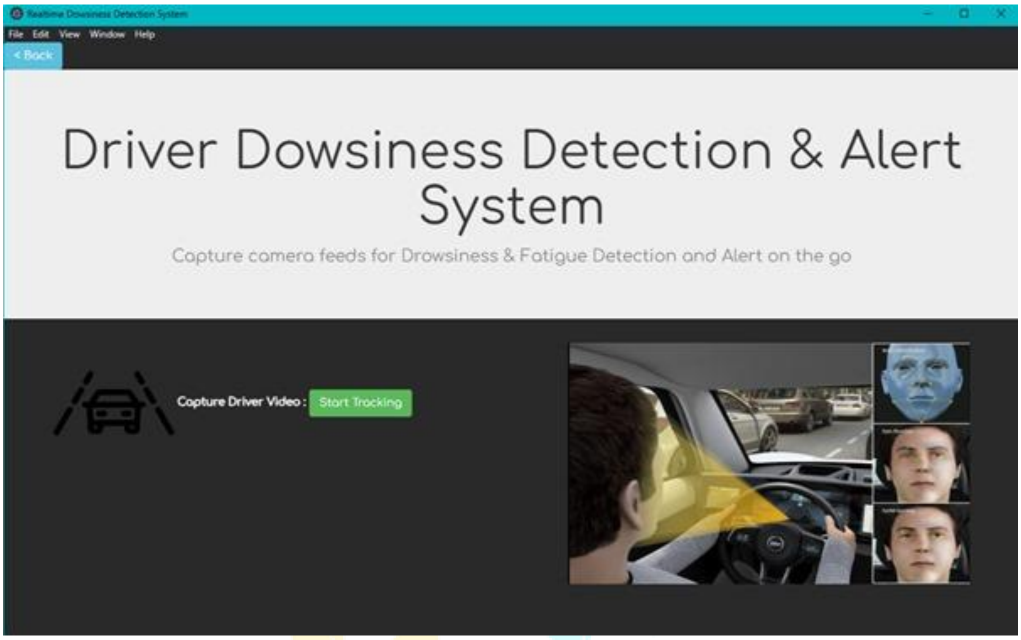

Figure 7 UI to start the detection system

Figure 8 Driver with Eyes Closed and value above threshold

As shown in figure 8, if the score is above 15, the dialog box shows that the driver is in a drowsy state in red, and our alarm will start beeping. But if the driver opens his or her eyes above the threshold score, i.e., 15, the score will start to decrease, and eventually the alarm will stop beeping when the score becomes less than or equal to 5.

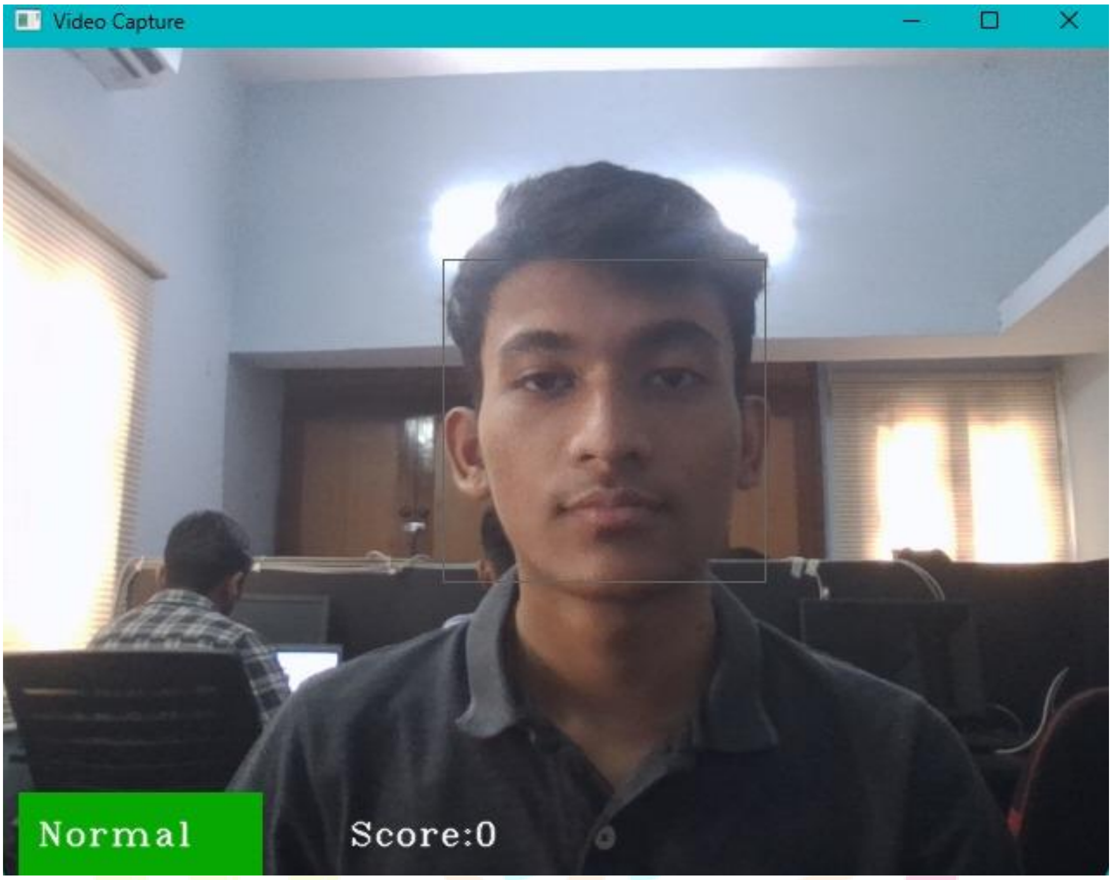

Figure 9 Driver with Eyes Open below threshold

As shown in Figure 9, if the score is less than 15 (because the threshold is set at 15), the dialog box shows that the driver is in a normal state in green.

I. Acknowledgment

We extend heartfelt gratitude to the researchers and authors whose seminal work provided the foundation for our project. We also acknowledge the organizers and sponsors of the conferences and journals where the cited research papers were presented and published. Their efforts in fostering academic exchange and disseminating knowledge have been invaluable.

Our appreciation extends to our mentors, colleagues, and friends for their unwavering support, encouragement, and constructive feedback throughout the project's duration. Their guidance and insights have played a pivotal role in refining our ideas and methodologies.

This project's success is a testament to the collective efforts and contributions of all those mentioned above. We are profoundly grateful for their support and assistance, without which this endeavor would not have been possible.

References

1. Klauer S G, Dingus T A, Neale V L, Sudweeks J D and Ramsey D J 2006 The impact of driver inattention on near crash/crash risk: an analysis using the 100-car naturalistic driving study data. Washington, DC: U.S. Department of Transportation, National Highway Traffic Safety Administration.
2. Akerstedt T, Kecklund G and Ho¨rte L G 2001 Night driving, season, and the risk of highway accidents. Sleep 24: 401–406.
3. Connor J, Norton R, Ameratunga S, Robinson E, Civil I, Dunn R, Bailey J and Jackson R 2002 Driver sleepiness and risk of serious injury to car occupants: population-based control study. Br. Med. J. 324: 1125–1129
4. Horne J and Reyner L 1999 Vehicle accidents related to sleep: a review. Occup. Environ. Med. 56: 189–294
5. May J F and Baldwin C L 2009 Driver fatigue: the importance of identifying causal factors of fatigue when Open-eye detection using iris–sclera pattern analysis1849 considering detection and countermeasure technologies. Transp. Res. Part F: Traf. Psychol. Behav. 12(3): 218–224
6. Wright N, Stone B, Horberry T and Reed N 2007 A review of in-vehicle sleepiness detection devices. Published Project Report PPR157, TRL Limited.
7. Bergasa L M, Nuevo J, Sotelo M A ´, Barea R and Guille´nM E L 2006 Real-time system for monitoring driver vigilance. IEEE Trans. Intell. Transp. Syst. 7(1): 63–77.

8. Oron-Gilad T, Ronen A and Shinar D 2008 Alertness maintaining tasks (AMTs) while driving. Accid. Anal. Prev. 40(3): 851–860
9. Papadelis C, Chen Z, Kourtidou-Papadeli C, Bamidis P, Chouvarda I, Bekiaris E and Maglaveras N 2007 Monitoring sleepiness with on-board electrophysiological recordings for preventing sleep-deprived traffic accidents. Clin. Neurophysiol. 118(9): 1906–1922
10. Faber J 2004 Detection of different levels of vigilance by EEG pseudospectra. Neural Netw. World 14(3–4): 285–290
11. Lin C T, Chang C J, Lin B S, Hung S H, Chao C F and Wang I J 2010 A real-time wireless brain computer interface system for drowsiness detection. IEEE Trans. Biomed. Circuits Syst. 4(4): 214–222
12. Wakita T, Ozawa K, Miyajima C, Igarashi K, Itou K, Takeda K and Itakura F 2006 Driver identification using driving behaviour signals. IEICE Trans. E89-D (3): 1188–1194
13. Takei Y and Furukawa Y 2005 Estimate of driver's fatigue through steering motion. In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, vol. 2, pp. 1765–1770
14. McCall J C, Trivedi M M, Wipf D and Rao B 2005 Lane change intent analysis using robust operators and sparse bayesian learning. In: Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). Washington, DC, USA: IEEE Computer Society, p. 59
15. Chang T H, Hsu C S, Wang C and Yang L K 2008 Onboard measurement and warning module for irregular vehicle behavior. IEEE Trans. Intell. Transp. Syst. 9(3): 501–513
16. D'Orazio T, Leo M, Guaragnella C and Distante A 2007 A visual approach for driver inattention detection. Pattern Recogn. 40(8): 2341–2355.
17. Suzuki M, Yamamoto N, Yamamoto O, Nakano T and Yamamoto S 2006 Measurement of driver's consciousness by image processing– a method for presuming driver's drowsiness by eye-blinks coping with individual differences. In: Proceedings of the IEEE International Conference on Systems, Man and Cybernetics, vol. 4, pp. 2891–2896.
18. Ji Q and Yang X J 2002 Real-time eye, gaze, and face pose tracking for monitoring driver vigilance. Real-Time Imag. 8(5): 357–377
19. Bretzner L and Krantz M 2005 Towards low-cost systems for measuring visual cues of driver fatigue and inattention in automotive applications. In: Proceedings of the IEEE International Conference on Vehicular Electronics and Safety, pp. 161–164.
20. Heinzmann J, Tate D and Scott R 2008 Using technology to eliminate drowsy driving. In: Proceedings of the SPE International Conference on Health, Safety, and Environment in Oil and Gas Exploration and Production.
21. Yang M, Kriegman J and Ahuja N 2002 Detecting faces in images: a survey. IEEE Trans. Pattern Anal. Mach. Intell. 24(1): 34–58.
22. Dowall J, Pavlidis I and Bebis G 2001 Face detection in the near-IR spectrum. Image Vis. Comput. 21: 565–578.
23. Zhu Z and Ji Q 2005 Robust real-time eye detection and tracking under variable lighting conditions and various face orientations. Comput. Vis. Image Und. 98: 124–154
24. Perez C A, Gonza´lez G D, Medina L E and Galdames F J 2005 Linear vs. nonlinear neural modeling for 2-D pattern recognition. IEEE Trans. Syst. Man Cybern. Part A: Syst. Hum. 35(6): 955–964
25. Rowley H, Baluja S and Kanade T 1998 Neural network-based face detection. IEEE Trans. Pattern Anal. Mach. Intell. 20(1): 23–38.
26. Rowley H, Baluja S and Kanade T 1998 Rotation invariant neural network-based face detection. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Santa Barbara, CA, pp. 38–44.
27. Jones M and Rehg J 2002 Statistical color models with application to skin detection. Int. J. Comput. Vis. 46: 81–96.
28. WangJGandSungE2002Studyoneyegazeestimation.IEEE Trans. Syst. Man Cybern. Part B: Cybern. 32(3): 332–350.
29. Y. -W. Chen and K. Kubo, "A Robust Eye Detection and Tracking Technique Using Gabor Filters," *Third International Conference on Intelligent Information Hiding and Multimedia Signal Processing (IIH-MSP 2007)*, Kaohsiung, Taiwan, 2007, pp. 109-112, doi: 10.1109/IIH-MSP.2007.58.
30. Ji Q 2002 3D face pose estimation and tracking from a monocular camera. Image Vis. Comput. 20(7): 499–511.
31. Li Y, Qi X and Wang Y 2001 Eye detection by using fuzzy template matching and feature-parameter-based judgement. Pattern Recogn. Lett. 22(10): 1111–1124.
32. Maio D and Maltoni D 2000 Real-time face location on grayscale static images. Pattern Recogn. 33: 1525–1539.
33. Viola P and Jones M 2001 Rapid object detection using a boosted cascade of simple features. In: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, vol. 1, pp. I-511–I-518.
34. Jagbeer Singh, Ritika Kanojia, Rishika Singh, Rishita Bansal, Sakshi Bansal , Driver Drowsiness Detection System – An Approach By Machine Learning Application , DOI: 10.47750/pnr.2022.13.S10.361
35. V B Navya Kiran , Raksha R , Anisoor Rahman ,Varsha K N ,Varsha K N ,Driver Drowsiness Detection , International Journal of Engineering Research & Technology (IJERT) ISSN: 2278-0181, Published by- www.ijert.org , NCAIT - 2020 Conference Proceedings
36. Mahek Jain, Bhavya Bhagerathi, Sowmyarani C N , Real-Time Driver Drowsiness Detection using Computer Vision , DOI: 10.35940/ijeat.A3159.1011121
37. Rohith Chinthalachervu, Immaneni Teja, M. Ajay Kumar, N. Sai Harshith, T. Santosh Kumar , Driver Drowsiness Detection and Monitoring System using Machine Learning ,doi:10.1088/1742-6596/2325/1/012057
38. Harshit Verma , Amit Kumar , Gouri Shankar Mishra , Ujjwal deep , Pradeep Kumar Mishra , Parma Nand , DRIVER DROWSINESS DETECTION , ISSN: 1004-9037 , https://sjcjycl.cn/ , DOI: 10.5281/zenodo.776772